Forecasting Returns of European Equity Mutual Funds: A Comparison of Classical Time Series Models and LSTM Neural Networks

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This study investigates the forecasting performance of classical time series models and Long Short-Term Memory (LSTM) neural networks in predicting the returns of European equity mutual funds over a historical period spanning from 1990 to 2024. The research is motivated by the increasing importance of accurate return forecasting for portfolio management, fund selection, and investor decision-making, especially in a market environment characterized by structural shifts, crises, and regime changes.

Among classical approaches, the analysis includes ARIMA (Autoregressive Integrated Moving Average) models and Exponential Smoothing (ETS) models in three standard variants: Simple Exponential Smoothing, Holt's Linear Trend method, and Holt–Winters Seasonal method. These models are selected due to their interpretability, well-established theoretical foundations, and frequent application in financial time series forecasting. As a benchmark for comparison, we use a passive buy-and-hold investment strategy, which reflects the performance of an investor who does not rely on any forecasting and simply holds the fund over time.

The study evaluates each model along two dimensions. First, we assess the quality of the forecasts using standard accuracy metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These measures allow for a quantitative comparison of predictive precision across different techniques and time horizons. Second, we implement simulated investment strategies that are guided by the forecasts of each model. The returns of these strategies are then compared to the buy-and-hold benchmark and to each other using multiple performance evaluation criteria.

Beyond cumulative return, the analysis considers a set of advanced performance statistics, including the Information Ratio (IR), Maximum Drawdown (MDD), Calmar Ratio, and Maximum Loss Duration (MLD). These measures capture not only the level of return but also the consistency and resilience of each strategy under adverse market conditions. By integrating forecast accuracy with actual investment

outcomes, we aim to provide a holistic assessment of model usefulness in real-world financial decision-making.

The study also incorporates a modern neural network approach — the Long Short-Term Memory (LSTM) architecture — which is particularly well-suited to modelling sequential and nonlinear dependencies in financial data. Unlike traditional models, LSTM networks can learn long-range time dependencies and complex temporal dynamics without requiring strict assumptions about stationarity or model specification. The LSTM is trained on historical return series using walk-forward validation to ensure robustness and avoid look-ahead bias.

Our findings suggest that while classical models offer satisfactory forecast accuracy and perform reasonably well in stable periods, the LSTM model could demonstrate greater adaptability and predictive power, especially during turbulent market phases. However, this improved performance often comes at the cost of reduced interpretability and greater computational complexity.

Overall, the results highlight the trade-offs between traditional and machine learning–based approaches to return forecasting. The findings may inform fund analysts, institutional investors, and financial advisors seeking to enhance the performance of actively managed portfolios through more effective forecasting techniques.